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CTS Tracking Performance Study

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Introduction to Tracking Performance Study

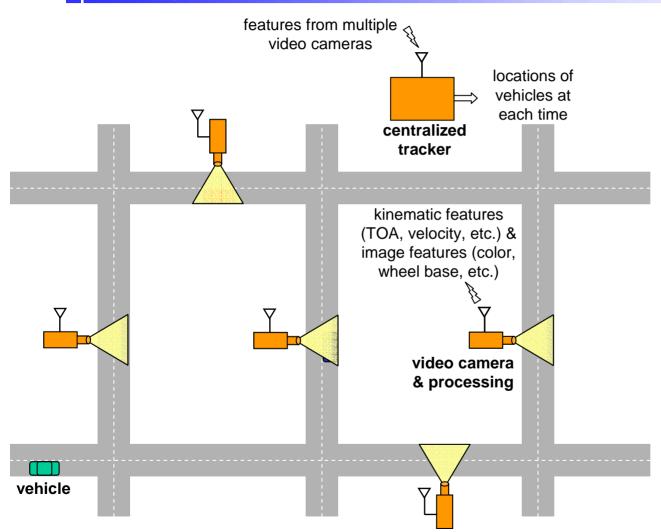
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- These results quantify feasibility of tracking vehicles over wide extents using multiple video cameras
- Study performed parametric tracking analysis
 - Given assumed video camera and processing capability (e.g., ability to match images from different cameras, spacing of cameras)
 - Given assumed vehicle characteristics (e.g., speed, maneuverability)
 - Given assumed background characteristics (e.g., traffic density)
 - How well can you keep track of vehicles?
- This briefing presents the concept, approach, and results of the study

Video Tracking CONOPS



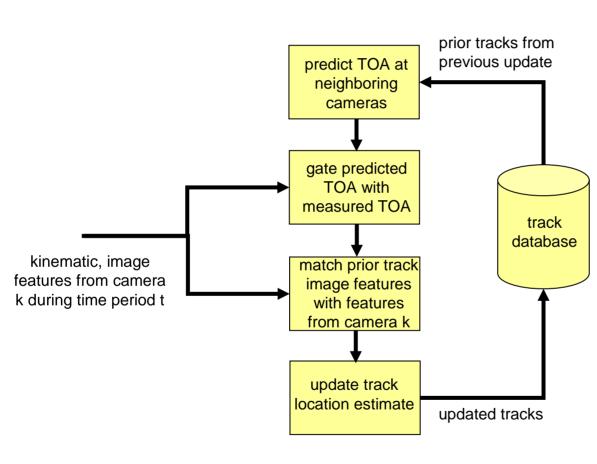
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Each video processor extracts vehicle kinematic features (e.g., time of arrival at the camera, instantaneous velocity, etc.) and image features (e.g., color, aspect ratio, wheel base, etc.) from the video stream, and sends the information to a centralized tracker which fuses the information and reports the estimated location of each vehicle in the system at each instant of time.

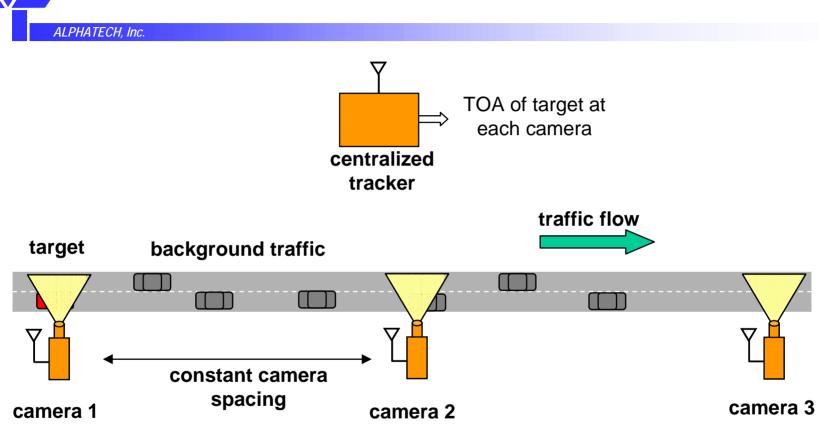
Tracker Functional Architecture





Based on current location estimate of a vehicle, the tracker predicts its TOA at nearby cameras, then compares the predicted TOA with measured TOA from each camera. Tracks that match TOA to within the predicted uncertainty pass the gate and are subsequently compared using image features. Tracks which have prior image features that match measured image features pass the matching and their location estimate is updated. The track database stores the current location estimate of each track together with estimated kinematic and image features.





Road network and sensor set up assumed for tracking performance analysis. One vehicle (red) is designated as target by camera 1; all other vehicles are background traffic. The tracking problem is to track the target as far as possible without confusing it with background traffic.



Tracking Performance Analysis Approach

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- Developed mathematical model of scenario
 - equally spaced cameras (parameter d is spacing)
 - vehicle motion satisfies second order stochastic difference equation (parameter q measures maneuverability)
 - probability of mismatching two vehicle images (parameter p)
 - measure time of arrival (TOA) without error at each camera
 - background traffic has homogeneous Poisson distribution (parameter rho)
- Simulated performance of multiple hypothesis tracking (MHT) algorithm based on the model
 - Kalman filter predicts TOA and MHT decides best track hypothesis based on likelihood ratio
 - varied depth of hypotheses (nscan parameter)
- Evaluated average tracking performance by Monte Carlo simulation of MHT



Video Tracking Performance-How the results were computed

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Results are from simulating a multiple hypothesis tracker

- MHT reports out most likely track hypothesis, based on likelihood ratio of hypothesis at each camera
- nscan=0,1,2,3 (i.e., maximum depth of hypothesis tree)
 - · no limit on breadth of hypothesis tree
 - nscan=0 is same as nearest neighbor tracker
- 1000 Monte Carlo simulations for each plotted point
 - error bar = 3 * maximum standard deviation for each probability, given 1000 Monte Carlos ~ +0.05 error bar

This is an actual tracker, not a performance model

- results represent lower bounds on probability of track length at least 10 km
- you could do better than this with a better tracker
 - (not better than 100%, of course)
- potentially achieve similar performance when the problem becomes more complicated (and realistic)

Tracking Performance-What's Plotted

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- Plot shows probability that track length is at least 10 km vs. camera spacing and misassociation probability
 - misassociation probability = probability of incorrectly matching a target and non-target given two camera observations
 - use values of 2 %, 4%, 8%, 16% for misassociation probability p
 - camera spacing varies from 100 to 1600 meters

Scenario

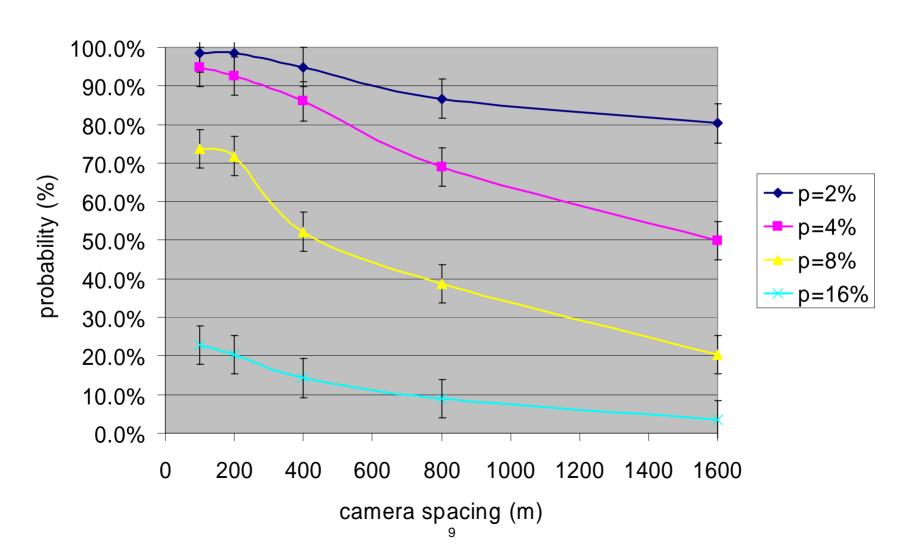
- one-way highway (no exit/entrance in between cameras)
- traffic flow density = rho (vehicles per second)
 - rho=0.5 means one car per 2 seconds
- speed predictability = q
 - q=10⁻⁷ corresponds to 2 m/s uncertainty per 316 m



Probability of Tracking at Least 10 km (rho=0.5 sec⁻¹,q=10⁻⁷ meters²/sec³, nscan=0)

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10 km probability (nscan=0)

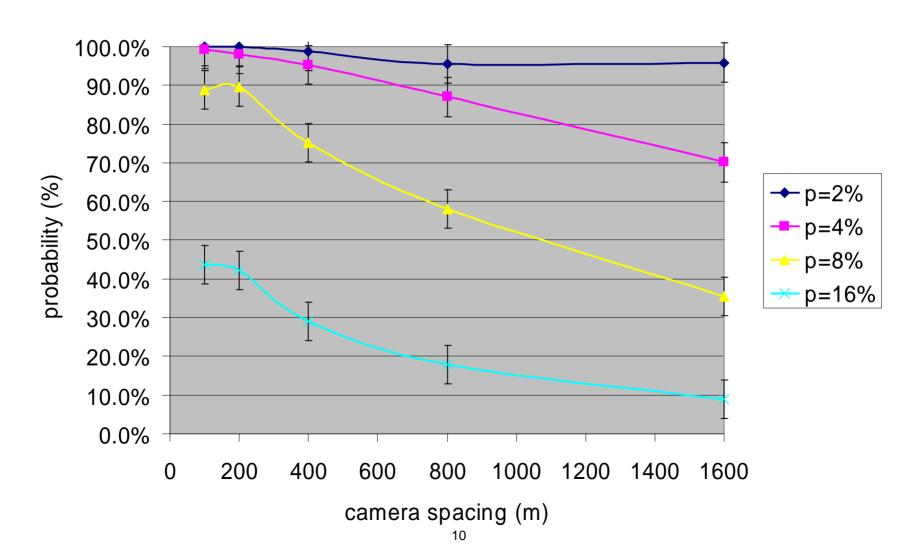




Probability of Tracking at Least 10 km (rho=0.5 sec⁻¹,q=10⁻⁷ meters²/sec³, nscan=1)

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10 km probability (nscan=1)

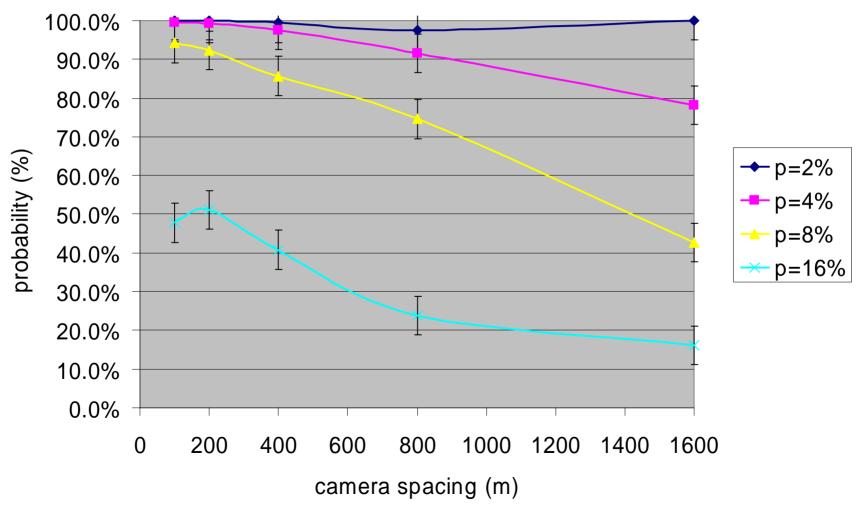




Probability of Tracking at Least 10 km (rho=0.5 sec⁻¹,q=10⁻⁷ meters²/sec³, nscan=2)

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10 km probability (nscan=2)

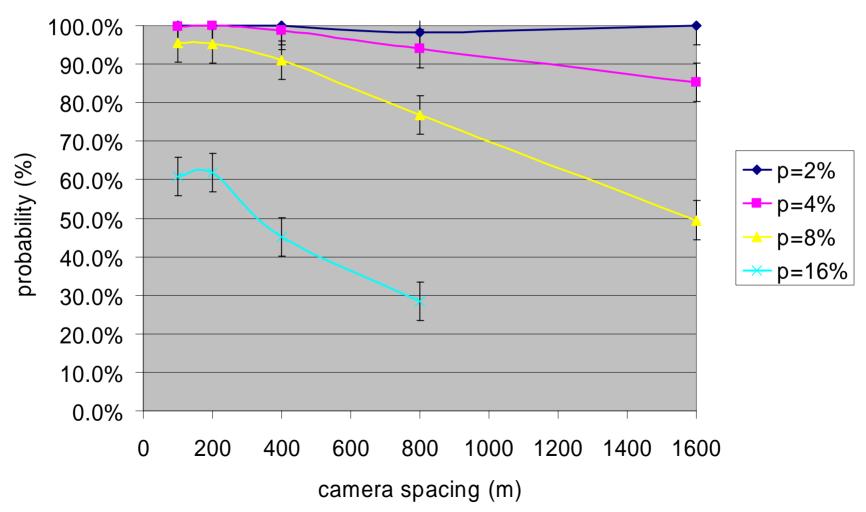




Probability of Tracking at Least 10 km (rho=0.5 sec⁻¹,q=10⁻⁷ meters²/sec³, nscan=3)

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probability of 10 km (nscan=3)





Conclusions of Tracking Study

- Current tracking technology with sufficient video matching performance is likely to give good tracking performance (track vehicles for at least 10 km)
- Requirements to achieve performance
 - camera spacing 400 meters for 90% tracks, 1600 meters for 50% tracks
 - camera-to-camera image matching performance with 8% or less probability of error
 - current tracking technology (e.g., MHT, Kalman filters)

Additional Considerations



- Need to incorporate more realistic assumptions about vehicle motion and road networks
 - speed change, stopping, turning
 - complex road networks
- Additional tracking performance metrics need to be considered and evaluated
- Additional evaluations needed
 - processing, communication requirements for real-time tracking
 - sensitivity to information about road networks
 - effect of sensor placement in complex road networks
 - and many others!